Physical Layer IEEE 802.11 Channel Occupancy Rate Estimation

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***Abstract*—With the rapid growth of wireless communication networks, we are facing the challenge of integration of diverse wireless networks such as WLAN and WWAN. Therefore, it becomes important to think at vertical handoff solution where the user can move seamlessly among various type of networks, to provide the best QoS to the higher layers applications. In this paper, we propose a method to estimate the channel occupancy rate metric of an IEEE 802.11 network from the physical layer. This method can be applied for any network that use the CSMA/CA protocol. Our theorical results are validated using experimental measurements captured by RAMMUS RF Plateform.**

***Index Terms*—Vertical handover, channel occupancy rate, IEEE 802.11.**

I. INTRODUCTION

Wireless communication devices become more popular and pervasiveness. These devices are used for a wide range of multimedia applications, which continually require a high QoS (quality of service) to achieve the expected performance by the user.

In homogeneous cellular systems, the link quality is keeped continuously by searching the best neighboring cell to associate to. The signal to noise ratio is then used as a common metric. When the base station giving the best link quality is found, a horizontal handoff occurs and the connection is transfered between the two base stations.

When the number of users connected on a given networks increases, the effective available bandwidth is affected. To maintain the QoS required by the higher layer application, and benefiting from the coexistence of various wireless networks, the users should roam freely from one interface to an other without any disturbing. This important process is referred as *vertical handover*.

The vertical handover is a very important capability in the future wireless communication era, where an integrated network including multiple technologies will try to offer a global broadband access to mobile users. However, compared to the horizontal handover, the signal strength metric is sometimes not suited and often not sufficient to appropriately trigger the vertical handover : as heterogeneous networks have different system characteristics, their performance cannot be simply compared by using the signal strength of two cells [1].

Within this framework, this paper aims at defining an efficient estimation method for a metric that can informs us on the channel occupancy rate of an IEEE 802.11 network. The originality of this method relies on the fact that this metric is estimated from the physical layer instead of the MAC layer as proposed in [1], [2], which represent a large gain of time and complexity.

In [1], [2] it has been highlighted that the usage of the channel bandwidth in a WiFi system can be approximated as the ratio between the time in which the channel status is busy according to the NAV (Network Allocation Vector) settings and the considered time interval. Indeed, prior to transmitting a frame, a station calculates the amount of time necessary to send the frame based on the frame's length and data rate. The station places a value representing this time in the duration field in the header of the frame. From the above description we can see that the NAV busy state can well reflect the traffic load. The higher the traffic, the larger the NAV busy occupation, and vice versa. Therefore, if we observe a NAV value during a certain time window, the available bandwidth and access delay can be estimated given a certain packet length [3].

The matter with this method is that it requires to be connected to the access point in order to have access to the NAV duration from the header, this may increases the decision time if many standards or Access Point (AP) are detected. In this paper, we propose a method that requires no connection to the AP, and no NAV duration reading. This technique is based on a physical layer sensing : Considering that the medium is free when only noise is observed and occupied when signal plus noise samples are observed (data frame), we use a likelihood function that can distinguish the signal plus noise samples from the one corresponding to noise only. Once we get the number of signal plus noise samples, a simple ratio processing can inform us on the network occupancy rate.

II. MODEL STRUCTURE

In the rest of the paper, we assume that IEEE 802.11 access points are detected. An IEEE 802.11 communication is based on a collision avoidance medium access protocol. Between two consecutive frames we have different inter frame spacing (IFS) intervals which guarantee different types of priority. At the receiver side, the observed signal is a succession of frames of noise samples corresponding to the IFS intervals or idle periods and of data frames (signal plus noise).

For clarity reason, we assume in this section that we have only one data frame in the observation duration (N_s samples) and explain in section III the proposed algorithm to locate it.

Consider that our receiver is doted of N antennas and let $\mathbf{y}_i = [y_i(1), \ldots, y_i(N_s)]$ be a set of N_s observations on the i^{th} antenna such that

$$\begin{cases} y_i(n) = w_i(n) & 1 < n < n_1 - 1 \\ y_i(n) = x_i(n) & n_1 < n < n_2 \\ y_i(n) = w_i(n) & n_2 + 1 < n < N_s \end{cases} \tag{1}$$

where $x_i(n)$ is the based band sample being received on the i^{th} antenna at the instant n, expressed as

$$x_i(n) = \sum_{k=0}^{L-1} h_i(k) s(n - n_1 - k) + w_i(n) \tag{2}$$

where $s(n)$ denotes the n^{th} transmitted symbol, with $\mathbb{E}[|s(n)|^2] = \sigma_s^2$. $h_i(k)$ is the channel response between the source signal and the i^{th} antenna. L is the order of the channel, and $\sum_0^{L-1} \sigma_{h_i(k)}^2 = 1$. $w_i(n)$ is a complex additive white gaussian noise with zero mean and variance σ_w^2.

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III. Frame localisation

As presented in the previous section, the vector $\mathbf{y}_i$ can be divided into three parts : noise , signal plus noise and noise. Starting from the set of observation $\mathbf{y}_i$ we want to find which samples correspond to noise and which ones correspond to signal plus noise. Since the samples are supposed to be independent in the noise areas, and correlated in the signal plus noise area we propose to use a likelihood function that informs us on the independance of the processed sample.

Let now $\mathbf{Y}_i(u)$ denotes the following set of observations

$$\mathbf{Y}_i(u) = [y_i(u), \ldots, y_i(N_s)] \qquad 1 \leq u < N_s \tag{3}$$

And let us define f_Y the joint probability density function of $\mathbf{Y}_i(u)$. If $\mathbf{Y}_i(u)$ is composed of only noise samples : $f_Y(\mathbf{Y}_i(u)) = \prod_{m=u}^{N_s} f_w(y_i(m))$, where f_w is the probability density function of a complex normal law centered of variance σ_w^2. The variance σ_w^2 is assumed to be known or at least estimated by a subspace-based algorithm [4].

The log-likelihood that the vector $\mathbf{Y}_i(u)$ is formed of $(N_s - u)$ noise independent samples is expressed as

$$\mathcal{L}_i(u) = \log \left[\prod_{m=u}^{N_s} f_w(y_i(m)) \right] \tag{4}$$

Computing the mean of the N log-likelihood functions expressed on each sensor, we get a criterion $\mathcal{J}(u)$ that informs us on the independence of the processed samples

$$\begin{aligned} \mathcal{J}(u) &= \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}_i(u) \\ &= -(N_s - u)\log(\pi\sigma_w^2) - \frac{1}{N\sigma_w^2} \sum_{i=1}^{N} \sum_{m=u}^{N_s} |y_i(m)|^2 \end{aligned} \tag{5}$$

As u varies in the interval $[1, n_1)$, the number of noise samples composing $\mathbf{Y}_i(u)$ decreases and so does $\mathcal{J}(u)$ until it reaches a minimum bound at n_1.

However, for u varying from n_1 to n_2 the number of signal plus noise samples decreases, therefore the ratio noise samples over signal plus noise samples increases and by the way $\mathcal{J}(u)$ increases. It reaches its maximum value while $\mathbf{Y}_i(u)$ contains only noise samples, i.e when $u = n_2$.

Finally for $n_2 < u < N_s$, $\mathcal{J}(u)$ decreases again for the sames reasons than the one explained for $1 < u < n_1$.

IV. Estimation of the channel occupancy rate

We propose to get the channel occupancy rate by a physical layer sensing. Indeed, while observing a set of N_s samples, if we can estimate the number of samples corresponding to signal plus noise (i.e the length of the data frame), we can easily estimate the channel occupancy rate.

When we have only one data frame in the observed window the occupancy rate can easily be estimated thanks to the previous criterion by $\frac{\hat{n}_2 - \hat{n}_1}{N_s}$. However, the assumption to have only one frame in the duration window is too restrictive. In practice we may get a signal as shown in figure 1 or with more frames. Based on the behavior of $\mathcal{J}(u)$, we can clearly see (fig 1) that the slope of $\mathcal{J}(u)$ is positive when u corresponds to the index of a signal plus noise sample and negative when u corresponds to the index of a noise sample. Therefore, we can take advantage of the gradient of $\mathcal{J}(u)$ to distinguish the nature of our observed samples. Introducing the function $\Phi(u)$ such that

$$\Phi(u) = \frac{1}{2}\left[\text{sign}\{\nabla(\mathcal{J}(u))\} + 1\right] \tag{6}$$

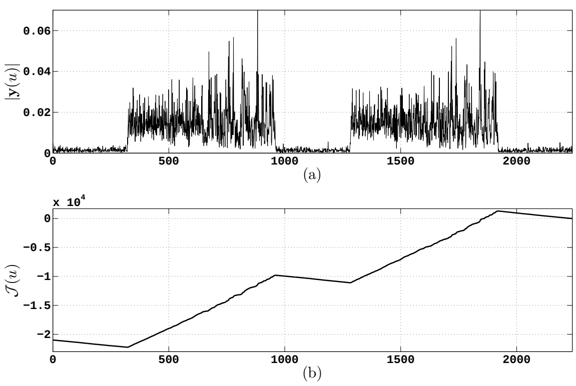

Fig. 1. (a) Absolute value of a wifi signal, (b) corresponding behavior of the criterion $\mathcal{J}(u)$

Here we denote by ∇ the gradient of $\mathcal{J}(u)$ processed using the central difference method, such that the derivative for any point of index $u \notin \{1, N_s\}$ is processed as $\nabla(\mathcal{J}(u)) = \frac{1}{2}\left(\mathcal{J}(u+1) - \mathcal{J}(u-1)\right)$. For the first point, we use the forward finite difference, and at the left end element the backward difference is used. sign$\{.\}$ denotes the sign operator. Therefore, $\Phi(u)$ equals to 1 when signal plus noise samples are present and zero when it is only noise, and the channel occupancy rate is estimated by

$$\widehat{Cor} = \frac{1}{N_s} \sum_{u=1}^{N_s} \Phi(u) \tag{7}$$

The difficulty is to estimate the channel occupancy rate accurately for low signal to noise ratio. In fact, there are fluctuations that can mislead the decision for a given sample. To fix this problem, we propose to use a smoothing technique.

V. Smoothing methods

We can either smooth the criterion $\mathcal{J}(u)$ or the function $\Phi(u)$. The two smoothing methods are presented in the next subsections.

A. Criterion $\mathcal{J}(u)$ smoothing

As said previously, in the signal plus noise frame there are fluctuations that mislead the decision for some samples. We propose here to smooth $\mathcal{J}(u)$ thanks to a polynomial interpolation of first order. Given a certain length of the smoothing window we search for the extrema of $\mathcal{J}(u)$ in this window and join them by a line, once it is done we slide the window with no overlapping until all the samples are treated. The procedure is illustrated in algorithm 1. The choice of the length of the smoothing window W is very important. Indeed, the algorithm do not behave correctly if we have multiple maximum or minimum of $\mathcal{J}(u)$ in the same window. To avoid such situation, we choose W equal to the length of a SIFS (for Short IFS) which is the smallest inter frame gap. Thus, theoretically we can't get a set of successive noise samples of a length less than a SIFS, and by the way we avoid multiple extrema in the same window.

B. Function $\Phi(u)$ smoothing

Here we propose to smooth $\Phi(u)$ directly. As presented below, theoretically we can't get a set of successive noise samples of a length less than a SIFS. Then, if it happens, it means that the algorithm took the wrong decision and $\Phi(u)$ will be forced to 1 for those samples. Practically, to avoid confusion it is judicious to choose a smoothing window less than a SIFS.

Algorithm 1 Smoothing algorithm

for $k = 1 : W : N_s - W$ **do**
  $\mathcal{J}_w = \mathcal{J}(k : k + W)$ `% select W samples`
  $(\mathcal{J}_{wmin}, u_{min}) = \min(\mathcal{J}_w)$ `%value and index of the minimum`
  $(\mathcal{J}_{wmax}, u_{max}) = \max(\mathcal{J}_w)$ `%value and index of the maximum`
  $I = [k, k + W, u_{min}, u_{max}]$ `%index vector`
  $I = \text{unique}(I)$ `%remove all the repeated values`
  I=sort(I,'ascend') `%sort I in the ascending order`
  $\mathcal{J}_s$ =[];
  for $t = 1 : \text{length}(I) - 1$ **do**
    $\mathcal{J}_s = [\mathcal{J}_s\ \mathcal{J}(I(t)) + \frac{\mathcal{J}(I(t+1))-\mathcal{J}(I(t))}{I(t+1)-I(t)}([0 : I(t+1) - I(t)])]$
    `%join the points by a line`
  end for
end for

The matter of fluctuations, drives us to search the conditions which makes the criterion an increasing function for signal plus noise samples and decreasing for noise samples. In the next section, we show that is possible only for a given range of the noise variance.

VI. Criterion validation limits

In this section, we propose to investigate the limits of the proposed criterion $\mathcal{J}(u)$. The aim is to find the dynamic where $\mathcal{J}(u)$ do well behave, i.e where its slope is positive for signal plus noise samples and negative for noise samples.

For $1 \le u \le n_1$: $\mathcal{J}(u)$ decreases only if $\frac{\partial \mathbb{E}[\mathcal{J}(u)]}{\partial u} < 0$, and therfore if

$$\mathbb{E}[\mathcal{J}(u)] = -(N_s - u)\log(\pi\sigma_w^2) - \frac{1}{\sigma_w^2}[(n_1 - u)\sigma_w^2 + (n_2 - n_1)(\sigma_w^2 + \sigma_s^2) + (N_s - n_2)\sigma_w^2]$$

the derivative costs : $\frac{\partial \mathbb{E}[\mathcal{J}(u)]}{\partial u} = \log(\pi\sigma_w^2) + 1$, and we get $\sigma_w^2 < \frac{1}{\pi e}$.

For $n_1 \le u \le n_2$: $\mathcal{J}(u)$ is an increasing function only if $\frac{\partial \mathbb{E}[\mathcal{J}(u)]}{\partial u} > 0$, then if

$$\mathbb{E}[\mathcal{J}(u)] = -(N_s - u)\log(\pi\sigma_w^2) - \frac{1}{\sigma_w^2}[(n_2 - u)(\sigma_w^2 + \sigma_s^2) + (N_s - n_2)\sigma_w^2]$$

the partial derivative is :

$$\frac{\partial \mathbb{E}[\mathcal{J}(u)]}{\partial u} = \log(\pi\sigma_w^2) + \frac{1}{\sigma_w^2}(\sigma_w^2 + \sigma_s^2) \tag{8}$$

and $\mathcal{J}(u)$ increases only if $\sigma_w^2 > \frac{1}{\pi e^{(1+\gamma)}}$, where $\gamma = \frac{\sigma_s^2}{\sigma_w^2}$.

For $n_2 \le u \le N_s$: we get the same result as for $1 \le u \le n_1$.

As a conclusion for an optimal behavior of $\mathcal{J}(u)$, the noise variance must satisfy

$$\frac{1}{\pi e^{(1+\gamma)}} < \sigma_w^2 < \frac{1}{\pi e} \tag{9}$$

This inequality represents the limits of the proposed criterion. It means that, the performance of the proposed method depends on the noise variance value, and also on the signal to noise ratio. Therefore, if the noise variance do not satisfy (9), we can think to adjust it applying a certain gain on the received signal. This alternative requires to know the signal to noise ratio which is not always possible. Another approach is to introduce a new criterion that get around this matter, this criterion is the distance between $\mathcal{J}(u)$, and a Parzen estimator based criterion introduced in the next section.

VII. Parzen estimator based criterion

The proposed solution, consists in processing a new criterion that aims to minimize the distance between the true p.d.f of the noise and a Parzen estimator estimated p.d.f of the observed samples. Starting from the set of observations $\mathbf{y}_i$ for $i = 1, \ldots, N_s$ and deviding the samples into their real part $p_i(n)$ and imaginary part $q_i(n)$, we get $2NN_s$ samples available for estimating the Parzen window density distribution. Given a sample $y_i(n) = p_i(n) + j.q_i(n)$ its Parzen window distribution will be $\hat{f}(y_i(n)) = \hat{f}(p_i(n)).\hat{f}(q_i(n))$ where

$$\hat{f}(z) = \frac{1}{2NN_sF}\sum_{k=0}^{2NN_s-1} K\left(\frac{z - z_k}{F}\right) \tag{10}$$

K is the Parzen window kernel and F is a smoothing parameter called the bandwidth. This kernel has to be a suitable p.d.f function, we use Gaussian kernels with standard deviation one. The new processed criterion is :

$$\mathcal{J}_K(u) = \frac{1}{N}\sum_{i=1}^{N}\log\left[\prod_{m=u}^{N_s}\hat{f}(y_i(m))\right] \tag{11}$$

Once we get $\mathcal{J}_K(u)$, we measure the distance between $\mathcal{J}(u)$ and $\mathcal{J}_K(u)$ to obtain a new criterion

$$\mathcal{R}(u) = |\mathcal{J}(u) - \mathcal{J}_K(u)| \tag{12}$$

Then, $\mathcal{R}(u)$ is smoothed thanks to the proposed method in V-A, a new function $\Phi_K(u)$ is processed thanks to the equation 6, substituting $\mathcal{J}(u)$ by $\mathcal{R}(u)$. The obtained $\Phi_K(u)$ is also smoothed using the technique detailed in V-B, then the channel occupancy rate is processed thanks to the equation (7).

VIII. simulations

IEEE 802.11n signals are simulated. We recall that the IEEE 802.11n are 64 subcarriers OFDM signals with a cyclic prefix of length 16 [5]. The propagation channel $\{h(l)\}_{l=0,\cdots,L}$ has an exponential decay profile for its non-null component (i.e., $\mathbb{E}[|h(l)|^2] = Ge^{-l/\mu}$ for $l = 0, \cdots, L$) with $L = 2/3.D$, G is chosen such that $\sum_{l=0}^{L}\mathbb{E}[|h_k(l)|^2] = 1$, and the RMS delay spread is set to 25 percent of the cyclic prefix. The channel is assumed to be time variant with a Doppler frequency equal to 10 Hz .

As treated previously, the Channel occupancy rate is function of the behavior of $\mathcal{J}(u)$. In figure 2, we show the NMSE (Normalized Mean Square Error) of the estimation of the channel occupancy rate versus the SNR, the SNR is defined as SNR $= \frac{\sigma_s^2}{\sigma_w^2}\sum_{l=0}^{L-1}\sigma_{h_i(l)}^2$ and is assumed to be constant on each sensor. The results are averaged over $M = 1000$ Monte Carlo runs, and the NMSE is here defined as $\frac{1}{M}\sum_1^M\left(\widehat{Cor}_k - Cor\right)^2/Cor^2$, where $\widehat{Cor}_k$ is the channel occupancy rate estimated at the k^{th} realization and Cor is the real channel occupency rate. We can clearly observe that for a high SNR the error tends to zero, and thus we achieve a good estimation. The proposed method is compared to the CFAR (Constant False Alarm Rate) method with a probability of false alarm $P_{fa} = 10^{-3}$ and to the energy detector proposed by Urkowitz [6], with a $P_{fa} = 10^{-4}$. The cognitive terminal is supposed to be doted of $N = 2$ antennas.

The smoothed $\Phi(u)$ has the best performace followed by the Parzen estimator for low SNR and finally the smoothed $\mathcal{J}(u)$. Concerning $\mathcal{R}(u)$, it has the advantage of being independent of the noise variance value, its performance are the same for any value of σ_w^2 even if its does not satisfy (9).

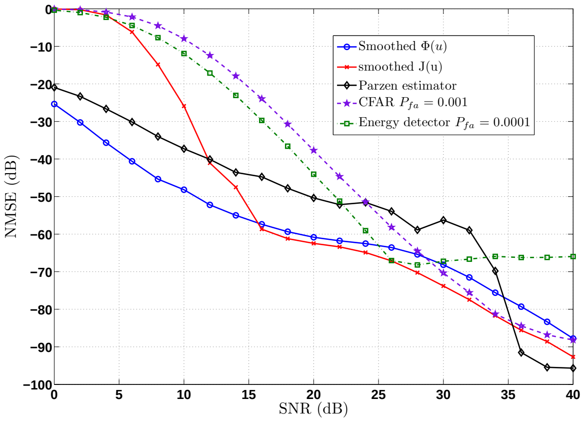

Fig. 2. NMSE of the channel occupency rate versus SNR

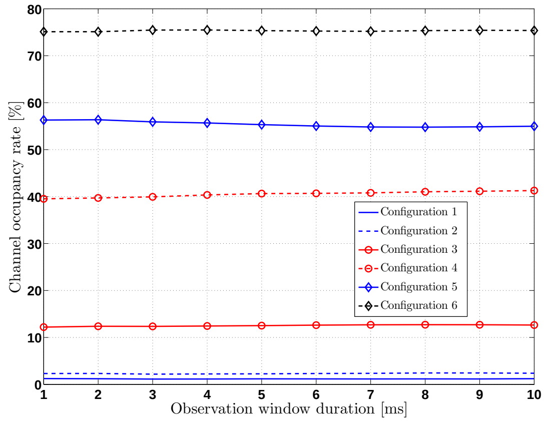

Fig. 3. Channel occupancy rate virsus the time observation window length

IX. Experimental Results

The proposed blind detection approach is evaluated using RAMMUS RF Plateform. Experiments were invistigated on the Channel 3 (2.422 Ghz) using the IEEE 802.11g norm. We tested differents schemes with diffent number of users varying the maximum bit-rate allocated to each one. The physical layer signal was captured thanks to an USRP2 device (Universal Software Radio Peripheral [7]), the sampling rate was set to 1 Mega-samples/sec[1]. We varied the observation window from 1ms to 10 ms. The tested scenarios are presented in table I, and the results are shown in figure 3. The presented results were averaged over 1000 non-correlated experiments. As explained previously the aim of the algorithm is to triger a vertical handoff toward the access point where the traffic is lower. According to the figure we can clearly see that the channel occupancy rate is lower in the configurations where a lower bit-rate is required by users, and increases as the required bit-rate and number of users increase. We also observe that a 2 ms observation window length is sufficient to get a decision, however, the shorter the observation window, the higher the variance of channel occupancy rate.

	number of users	max bit rate / user
Configuration 1	1	5 kB/s
Configuration 2	3	5 kB/s
Configuration 3	1	500 kB/s
Configuration 4	3	500 kB/s
Configuration 5	1	the whole bandwidth
Configuration 6	3	the whole bandwidth

TABLE I
Configuartions of the expimriments

X. Conclusion

In this paper we proposed a new method for estimating the channel occupency rate of an IEEE 802.11 network. This method is based on a physical layer sensing, this metric informs us on the MAC-layer QoS condition of the network, such as available bandwidth and access delay, which are good informations to perform a vertical handover. Computer simulation showed good results for the WiFi SNR operating range. Experimental results suport our simulations and show that the proposed technique is a good decision metric to trigger a vertical handover or even a horizontal handover between two access points.

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